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Detecting passenger discomfort from abnormal driving manoeuvres

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Abstract

Abnormal driving manoeuvres such as sudden braking, harsh acceleration or swerving can impose serious risks for people participating in the traffic. This study focuses on the detection of passenger discomfort by inferring the underlying abnormal driving events that cause such experiences. Experiments for threshold-based techniques are conducted on real world data collected from smartphones on heterogeneous cars and drivers, where the passengers provided discomfort annotations. Accurate detection is found on sudden acceleration events at 82% and hard braking events at 96%. By detecting these abnormal driving manoeuvres, drivers can be alarmed when their driving behaviours cause passenger discomfort.

Keywords:

abnormal driving behaviour, event detection, passenger discomfort.

1. Introduction

Unexpected driving manoeuvres (e.g. harsh acceleration, sudden stopping and swerving) are prominent sights on the roads. These driving patterns can incur a financial penalty to drivers even if no accidents occur in addition to the risk of engaging in crashes. Tyres and brakes may wear out faster, resulting in frequent needs for servicing and larger than normal fuel consumption. In general, humans behave more appropriately when being watched. Research has shown that even an illusion of being observed can make people act more responsibly [5]. We assume that this psychological effect also applies to driving, i.e., people will drive more responsibly when being monitored. We are interested in an application which requires analysing driving data in real time and raises red flags when abnormal events are detected. Discovering abnormal driving manoeuvres is challenging due to drivers' variability and subjectivity. In this paper, the abnormal driving events are defined by passenger discomfort.

1.1 Motivations

In many applications, insurance companies have started offering policies with telematics equipment. Once fitted in the car, the device may be used to assess driving behaviours for determining insurance premium. The collected data may also be used by traffic authorities to build road profiles and develop better road safety programs, products and policies. Despite the great progress in research [14] and availability of commercial products regarding the detection of abnormal driving behaviour, fundamental research questions regarding this area have remained largely unanswered. Firstly, most studies assume the availability of perfectly labelled data, which is not realistic. Secondly, several studies only provide estimated threshold. They do not specify accuracy on uncollected data. This practice can be over-optimistic. In particular, this approach may not be generalised on a larger scale of deployment for fitting the threshold due to certain constraints of a given collected data. Finally, this is the first study that includes recognition of swerving events. Existing works have only covered abnormal acceleration and deceleration (braking). More importantly, this research is infrastructure free in that it does not require additional hardware to be installed in vehicles. We utilise sensors in smartphones. Users are only required to install and activate the application in their smartphones to enable monitoring.

1.2 Research questions and contributions

This paper addresses the following main research questions:

- Detecting abnormal driving events (sudden acceleration, extreme braking and swerving) from a smartphone's accelerometer.
- Learning discomfort annotations that are given by vehicle passengers to define abnormal driving events in sensor data streams.

Hence, the contributions of this paper include:

1. Extended temporal segmentation technique for handling discomfort annotations.
2. Recognition of abnormal driving manoeuvres through threshold-based technique.

We present techniques to overcome noisy factors in data and possible incorrect annotations due to the data collection and human factors. Our approach achieved an average F-measure of 82% for detecting hard braking and 96% for extreme acceleration.

2. Background and related work

2.1 Related work

Detecting abnormal driving manoeuvres is an important research topic, due to its direct application in daily life. Such risky events on the road can incur deaths and serious injuries. As an example, more than 1,300 deaths occurred in the year 2012 due to traffic incidents according to Australian statistical summary report [3]. Although the number of deaths suffered from road crashes has decreased from 3,789 in 1970 to 1,155 in 2014 [1], both social and economical impacts are significant. It is also reported in [1] that the estimation of economic cost can reach up to approximately $27 billion a year. In order to improve the road safety, Australia launched its first large-scale study of everyday driving behaviours in April 2015 [12], namely Australian Naturalistic Driving Study (ANDS). The program aims to collect data from drivers in normal and safety-critical situations.

The three most widely studied driving events are extreme acceleration, braking and swerving. Other studies such as [7,8] analysed road condition such as bumps and potholes. The approaches using image processing are excluded from our study as we intend to use the smartphone as a processing station in real time scenario.

Nowadays, most consumer smartphones are integrated with standard 3-D inertial sensors, providing readings in three orthogonal directions: x-axis, y-axis, and z-axis. Engelbrecht et al. [4] clarified accelerometer as one of the most widely used sensors for analysing driving behaviour. Many studies use at least one orthogonal direction of accelerometer data. Several other studies combine accelerometer and gyroscope data for turn detection.

Mohan et al. [10] were the first to propose to detect unsafe driving behaviours using smartphones. Their application (Nericell) offers the capability to detect hard braking event by noting high mean x-axis acceleration. The algorithm searches over 4 seconds windows for mean acceleration exceeding 0.12*g*. However, their experiments require external accelerometer to communicate with the phone via Bluetooth. In the year 2008, accelerometer was not yet available widely in consumer smartphones. Mobile phone industry has gone through a major revolution since then.

Fazeen et al. [6] relied on the smartphone’s accelerometer readings to identify driving behaviours and road condition. In addition, observation was performed on acceleration in x-axis and y-axis to detect extreme acceleration and deceleration. If the acceleration exceeds ±0.3*g*, the event is reported as being abnormal. To detect lane change, they observed the acceleration of x-axis. The threshold at ±0.5*g* is decided based on their empirical experiment for left and right lane change respectively.

The differences in sampling frequency, phone orientation, and phone model affect classification result significantly. A high sampling frequency may increase power consumption and response time while a low frequency may cause information loss. Many studies have sampling frequency at 25Hz. Our study uses 10Hz, which is a low sampling frequency. However, our proposed techniques are able to detect abnormal driving events with high accuracy. In real world situation, having lower sampling frequency can help to preserve the battery life when a smartphone is used to perform real-time abnormal event detection.

Phone orientation has an important implication on which sensor channels to observe. For example, researcher A may suggest using x-axis acceleration while researcher B recommends z-axis acceleration. In [6], the Nexus One lies flat in the centre of the console, with the y-axis pointing to the front of the car and z-axis facing the roof. Holster and velcro are used to secure the phone position and orientation. An earlier study of [2] proposed the critical jerk method for detecting safety critical events based on built-in accelerometer data in the car. In this paper, we leverage this feature to detect abnormal driving manoeuvres based on passenger discomfort. Furthermore, our solution uses accelerometer from the smartphone, which is a cheaper and intuitive solution.

2.2 Accelerometer and driving events

Accelerometer is a device to measure the acceleration of an object. Suppose when a smartphone is facing upward on a table, the built-in accelerometer measures the reading of z-axis at around $-1g$. This value incorporates the force of gravity of Earth at $9.8 m/s^2$. In contrast, the accelerometer would read zero while an object is in free fall mode on the earth. Significant change in acceleration denotes abnormal driving events, which consist of:

1. **Acceleration:** The car starts from a standstill position or a constant stable speed and travels in a straight line with increasing speed. Passengers may experience linear acceleration as a force pushing them back into their seats.
2. **Braking:** The speed of the car decreases significantly to a low vehicle speed or full stop. In other words, it is associated with acceleration in the opposite direction. Passengers may experience deceleration as a force lifting them from their seats.
3. **Cornering/lane-changing:** The car turns to a new direction. This relates to acceleration in different directions (referred as non-linear acceleration). Passengers may experience a sideways force.

Jerk is defined as the rate of change of acceleration with respect to time [13]. It is also widely known as jolt, surge, or lurch. In this paper, we denote this term as *jolt*. The rapid change in vehicle acceleration imposes a significant jolt. The factors that cause discomfort and instability for passengers are extreme acceleration events, which result in abnormal jolts. The human brain maintains the body balance and the rest state of the mind depending on the situation of surrounding environment. This equilibrium can only be maintained if the brain has enough time to adapt to the changes. If the changes happen faster than the mind can react, the chain is temporarily broken until the brain reclaims control. Passengers in transportation would need time to adapt to sudden changes and therefore adjust the tension of their muscles in order to avoid losing the control over their body motion. In the case of standing passengers in public transport, any acceleration greater than $0.93 m/s^2$ will cause danger of falling when there is no support to hold within the vicinity. The largest jolt that an average human can withstand without losing the balance is $0.60 m/s^3$ [9].

3. Abnormal driving events

3.1 The intuition of driving event detection

Previously, the abnormal driving events are elaborated by the notion of acceleration. Thus, a threshold needs to be defined in between normal events and abnormal events.
However, this can be achieved under the following assumptions:

1. Data are perfectly labelled.
2. There is a clear definition for each type of event. For example, how abnormal is considered an extreme braking event; how bad is considered a swerving event.
3. Other events (not under consideration) do not fall into the same threshold range as our targeted events.

Through an extensive literature review, we found that almost all published research take these three assumptions for granted. Extreme acceleration and hard braking are generally considered abnormal events in which more force (beyond normal) is applied to the pedal. Due to the lack of benchmark data on this topic, all researchers presented their results using their own datasets.

In many cases, the definition of abnormal events tends to be subjective from the experiences of participants or annotators. Such abnormal driving manoeuvres may be risky in one experiment, while it could be normal in other experiments. In reality, achieving perfect labelling is almost impossible. Besides, labels are also subject to the aspect of human lag in annotating the data. Even if the data are not annotated in real time, one of the recommended approaches is to examine the sensor reading manually in order to highlight start and end points of an event. This process can also be guided by the annotations generated by the domain experts.

For the purpose of our studies, it is not required to overcome all the above assumptions. Hence, we offer to digest the problem from a different perspective. These abnormal events are viewed as the causes of passenger discomfort.

3.2 Formal problem statement and assumptions

The problems are formulated from the subject of detecting passenger discomfort associated with an abnormal driving event. In this case, a smartphone is used both as the sensing platform and the processing station. The analysis and detection were conducted on real data collected with the settings composed of nine drivers and three different car models. The dataset is fully labelled with passenger's self-annotations through a mobile application.

Our work is subject to the following assumptions:

1. The road condition is reasonably good. Bumpy roads are treated as noise.
2. There is human lag in labelling. It is due to our data collection protocol. We will present ways to compensate for this.
3. There can be misannotations, either false alarms or false dismissals.

Problem statement 1: Temporal segmentation of abnormal driving event derived from annotations of passenger discomfort.

The abnormal driving manoeuvres are flagged from the passengers when they feel uncomfortable during a driving session. In this paper, the terms of extreme, hard and sudden are interchangeable for abnormal acceleration and braking events. Performing temporal segmentation on data that are associated with passenger discomforts is challenging due to the subjectivity of the annotators. Therefore, reasoning with search space of the events is needed before we attempt to extract features to detect abnormal driving manoeuvres. These discomfort annotations would define the range of abnormal driving events.

Problem statement 2: Detecting passenger discomfort that is associated with an abnormal driving event by noting a high change in acceleration.

In the scenario that involves aesthetic discomfort of a passenger, acceleration of a vehicle is defined as the main feature in our experiments. Hence, discomfort is provided through annotations from passengers. The derived abnormal driving events: extreme acceleration, hard braking and swerving are associated with high changes in vehicle motion. In this case, passenger discomfort is caused by the discontinuity in acceleration that results in large jolt. By observing the data distribution between events and non-events, we can identify users' tolerance level (threshold to detect abnormal events). Simple, intuitive and suitable techniques are required for real-time monitoring and assessment of driver's behaviour.

4. Methodologies

4.1 Notation

In this paper, we use *Acc_x* to denote the acceleration in the x-axis, *Acc_y* for the acceleration in the y-axis and *Acc_z* for the acceleration in the z-axis. Note that these terms are concentrated to the acceleration of the device (the phone itself). Therefore, these exclude the effect of gravity from the pure reading of accelerometer data.

- A time series *T* is a sequence of data points recorded at uniform interval.
- *acc_threshold* is the threshold to discern an extreme acceleration from a normal acceleration.
- *brake_threshold* is a threshold to discern a hard braking from a smooth braking.
- *swerving_threshold* is a threshold to discern an extreme swerving from a smooth regular turning. *J* is the extracted jolt value. Jolt of a local point i is J_i.
- *mean_W* is the mean acceleration of a time series subsequence *W*.
- *S* is the region to extract feature. Human labelled regions are derived from passenger discomfort annotations. Thus, human lag is considered in our technique to extend the event region. For example, we may need to look at portions of the pre-event data points and/or portions of post-event data points. We call this the extended search area *S_extended*.

4.2 Extended area temporal segmentation

In this paper, we use *Acc_x* to denote the acceleration in the x-axis, *Acc_y* for the acceleration in the y-axis and *Acc_z* for the acceleration in the z-axis. Note that these terms are determined for the acceleration of the device (the phone itself). Therefore, these readings exclude the effect of gravity from the accelerometer data.

In order to extract features from sensor data streams, it is important to perform temporal segmentation in a certain mechanism. Extended area temporal segmentation is proposed to cope with the subjective annotations of an abnormal event. It incorporates *S_extended* as the length for temporal segmentation. *S_extended* is mainly composed of pre-event region (*Lag_before*), event region, and post-event region (*Lag_after*).

4.3 Threshold-based event detection

For threshold based event detection methods, the following device acceleration channels were used: 1) z-axis for detection of extreme acceleration and hard braking; 2) x-axis for detection of swerving. To detect extreme acceleration, the process involves calculation of certain threshold and mean acceleration over 4 seconds windows. Moreover, a feature called jolt was extracted from acceleration data for detecting extreme braking and swerving. Through empirical observation over data distribution, a jolt threshold that causes passenger discomfort was derived. This feature effectively distinguishes extremity of the target events from the course of normal driving behaviour. In threshold-based event detection, the threshold is derived from training datasets where events are identified based on discomfort annotations.

Threshold for extreme acceleration. We are interested in the mean acceleration in *S_extended*. The actual start point and actual end point of *S_extended* is decided similarly to the case of hard braking event. The only difference is that we set *Lag_after* and *Lag_before* both equal to 10 (10 data points ≈ 1 second). The final threshold value is computed as:

$$acc\_threshold = mean(acc_1, acc_2..., acc_n) \quad (1)$$

in which acc_1 is the mean acceleration of the first extreme acceleration event; n is the total number of labelled extreme acceleration events in the observation set.

Threshold for hard braking. Due to our device's orientation (Figure 2), we use acceleration reading in z-axis *Acc_z* for detecting extreme acceleration and deceleration events. To calculate jolt, we take the next reading of acceleration subtracting the previous acceleration value, divided by the time difference. The slope can be calculated through the difference in adjacent points. However, the noise from accelerometer would affect the calculation. This can be fixed by the smoothing technique, or by considering the difference in adjacent regions. To measure jolt for a local point, we look k points behind and k points ahead. The difference in the means of these two regions becomes the jolt value of that point. We set $k = 5$ through empirical experiment.

$$J_i = mean(Acc\_z_{i:(i+k)}) - mean(Acc\_z_{(i-k):i}) \quad (2)$$

An important observation is that because of the human lag, the region we need to search for features is larger than a one to one mapping. The starting point and ending point of *S_extended* are calculated as follow.

$$Actual\_start\_point = S\_start\_point - Lag\_before \quad (3)$$

$$Actual\_end\_point = S\_end\_point + Lag\_after \quad (4)$$

where *S_start_point* is the original starting point, and *S_end_point* is the original ending point of labelled region *S*. Figure 1 shows *S_extended* (marked as "Region to search for features") for a sudden braking event.

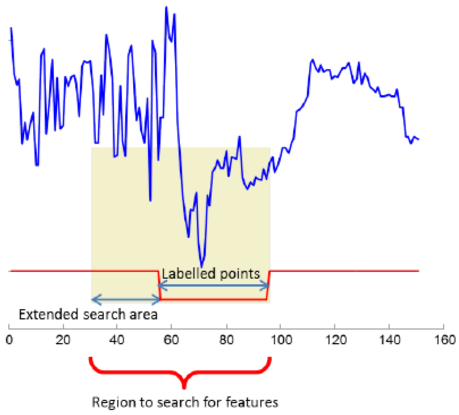

Figure 1 – *S_extended* (Extended search area) for a hard braking event

Non-event regions are any regions that do not contain a targeted event. For example, in the case of hard braking search, non-event regions are all regions excluding the hard braking regions. The starting point and ending point of a non-event are calculated as the following:

$$Actual\_start\_point = Lag\_after + k + Start\_point \quad (5)$$

$$Actual\_end\_point = End\_point - k - Lag\_before \quad (6)$$

where *Start_point*, *End_point* are original starting/ending points of a non-event region.

For detecting a hard braking event, the previous one second was taken into consideration. As we sample data at 10Hz, this is equivalent to setting *Lag_before* = 10. We do not see any importance in searching after the labelled region, and therefore we set *Lag_after* = 0. Jolt value of a hard braking event is the maximum jolt found within *S_extended*. Jolt value of normal driving is derived from points randomly sampled in the non-event regions. The final threshold value is computed as:

$$brake\_threshold = min(brake_1, brake_2..., brake_n) \quad (7)$$

where $brake_1$ is the jolt value of the first hard braking event; n is the total number of labelled hard braking events.

Threshold for Detecting swerving. The jolt feature to detect swerving event can be computed through Equation 8. Therefore, we are particularly interested with x-axis of the accelerometer in absolute measurement due to bidirectional steering (left-right) during a swerving event.

$$J_i = abs(mean(Acc\_x_{i:(i+k)}) - mean(Acc\_x_{(i-k):i})) \quad (8)$$

Hence, the swerving threshold value can be computed as the following:

$$swerving\_threshold = min(swrv_1, swrv_2..., swrv_n) \quad (9)$$

where $swrv_1$ is the jolt value of the first swerving event; n is the total number of annotated swerving events.

5. Experimental setup

5.1 Data collection and pre-processing

Data collection was conducted on a remote racecourse with nine volunteers as expert drivers. Throughout the day, there were three cars used when executing a driving task. The passenger in each car performed annotation by marking the abnormal driving events that are associated with personal discomfort.

The data collection was conducted with the presences of both Apple iPhone and Android phones (Figure 2). However, the experiments in this paper are presented by analysis of iPhone data only for simplicity reason. The recordings include the streams of inertial sensor channels derived from the Apple Motion Framework. However, we only use user-motion-acceleration for the task at hand. It is accelerometer reading (sampling frequency at 10Hz) with the effect of gravity filtered out. Thus, it reflects the pure acceleration of the vehicle. We only use the reading in the z-axis to detect extreme acceleration and braking events.

Figure 2 - Mobile devices are attached to the windshield of the car.

5.2 Statistical observation

Extreme acceleration. Mean values were calculated within *S_extended*. Figure 3 shows the average value of each extreme acceleration event. The calculated mean values are relatively spread out, ranging from -1.3181 to 2.9101. The average of all events is 1.2132 and STD being 1.2208. The mean value of acceleration event is then derived as *acc_threshold*.

Hard braking. Figure 4 shows the distribution of hard braking events and normal events. We can see that hard braking events and normal driving have very different jolt values. The highest frequency for jolt of normal driving is around 0. Jolt values for normal driving are always less than 1 while all hard braking events are having jolt values greater than 2. The minimum jolt for a hard braking event is 2.0336 (derived as *brake_threshold*).

Swerving. From the distribution shown in Figure 5, we can see a distinct difference between normal and swerving events based on minimum jolt value of swerving events and maximum jolt value of normal events. Therefore, we derived 1.4 for *swerving_threshold*.

For each observation above, normal events are taken from non-event regions. In order to cope with the notion of imbalance proportion in distribution, normal event region is sampled once in every non-event region.

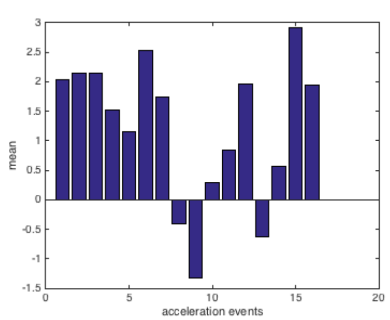

Figure 3 - Mean acceleration values of extreme acceleration events

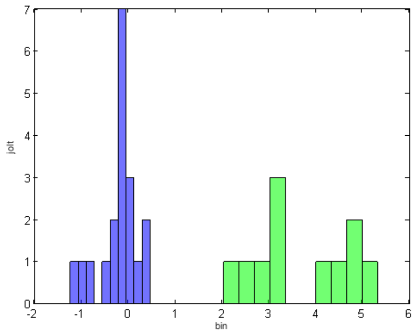

Figure 4 - Histogram of jolt frequencies for hard braking and non-braking events

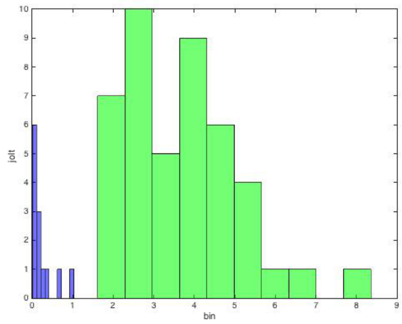

Figure 5 - Histogram of jolt frequencies for swerving and non-swerving events

5.3 Algorithm for threshold-based event detection

In detection/testing, sliding window is used to sample the test time series. For each time series (corresponding to a driving session), observation is performed on each window *W* at a time, then move by step size *S* in every iteration. The algorithms are formalized as shown below.

```
for each window W in time series T do
 calculate mean acceleration mean_W;
 if mean_W >= acc_threshold then
   report an extreme acceleration event;
 end
end
```

Algorithm 1 - Extreme acceleration detection (z-axis)

```
for each window W in time series T do
  for each point i in window W do
     calculate jolt J_i;
     if J_i >= brake_threshold then
       report hard braking;
       skip the rest, move to next window;
     end
  end
end
```

Algorithm 2 - Hard braking detection (z-axis)

```
for each window W in time series T do
  for each point i in window W do
     calculate jolt J_i;
     if J_i >= swerving_threshold then
       report swerving event;
       skip the rest, move to next window;
     end
  end
end
```

Algorithm 3 - Swerving detection (x-axis)

5.4 Evaluation metrics

F-measure (F-1) is used to justify the quality of event detection. F-measure is the measurement of detection accuracy by incorporating both precision and recall to produce harmonic mean [11]. True Positive (TP) is the portion of correctly detected abnormal driving events. False Positive (FP) is the portion of incorrectly detected target events, i.e. false alarm.

False Negative (FN) relates to Type II error where it denotes the portion of actual abnormal driving events that are marked as normal events.

$$\text{precision} = \frac{TP}{TP + FP}$$
$$\text{recall} = \frac{TP}{TP + FN}$$
$$\text{F-measure} = 2 * \frac{precision * recall}{precision + recall}$$

Figure 6 – Evaluation metrics

6. Results, evaluation and discussion

From the observation of data distribution, *acc_threshold* is set to 1.1536, *brake_threshold* is set to 2.0336 and *swerving_threshold* is set to 1.4. Based on these thresholds, we performed abnormal event detection on different test datasets.

The testing results are shown in Table 2 and Table 3. The average F-measure of extreme acceleration and hard braking indicates accurate detection of events at 96% and 82.8% respectively. However, our additional analysis revealed that the detection of swerving is not significantly accurate (F-1 = 57.3%) when threshold-based method is used. Therefore, we can conclude that threshold-based approach of event detection may not be suitable to detect a complex abnormal event where driver performs hard braking during swerving.

Table 2 – Test result for extreme acceleration

Session	**Detect**	**Truth**	**TPR**	**FPR**	**F-1**
1193	3	2	100%	1.2%	80%
5453	2	2	100%	0%	100%
6125	3	3	100%	0%	100%
9641	2	2	100%	0%	100%
9564	2	2	100%	0%	100%
Average					**96%**

Table 3 – Test result for hard braking

Session	**Detect**	**Truth**	**TPR**	**FPR**	**F-1**
1193	3	3	100%	0%	100%
5453	2	2	100%	0%	100%
6125	1	2	50%	0%	67%
9564	1	2	50%	0%	67%
9641	2	3	67%	0%	80%
Average					**82.8%**

7. Conclusion

In this paper, a method is proposed for the detection of abnormal driving behaviours by identifying significant changes in accelerometer readings. A threshold-based technique is introduced to allow us to recognise driving events that cause passenger discomfort. As a result, abnormal acceleration and braking events can be effectively detected. From our findings, threshold-based event detection is not suitable to detect a complex event such as swerving. In the future, machine learning techniques would be explored to detect these abnormal events.

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